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To cite this article: Birgit Zeyer-Gliozzo (2024) Returns to formal, non-formal, and informal further training for workers at risk of automation, Journal of Education and Work, 37:5-6, 382-402, DOI: [10.1080/13639080.2024.2447037](https://doi.org/10.1080/13639080.2024.2447037)

To link to this article: <https://doi.org/10.1080/13639080.2024.2447037>



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Returns to formal, non-formal, and informal further training for workers at risk of automation

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ABSTRACT

The automation of job tasks due to technological change increases the pressure on workers whose jobs consist largely of such activities. In this context, politics and science attach great importance to further training, although the benefits for affected workers have hardly been investigated. Drawing on human capital theory and the task-based approach, this study examines the effect of further training on job tasks and the probability of automation for workers at risk of automation. These are workers who (a) work in routine intense jobs or (b) have a high probability of automation, based on the expert assessment of the automatability of occupations by Frey and Osborne (2017). Using data from the German National Educational Panel Study (NEPS), fixed-effects models are estimated to account for unobserved heterogeneity. The results show that informal further training is most effective in increasing non-routine tasks and reducing routine tasks and the probability of automation. Formal and non-formal training also show returns in some cases, although these are often not significant. The results thus suggest that not all forms of further training are helpful in adapting to new demands in the course of technological change and provide starting points for future research.

ARTICLE HISTORY

Received 30 September 2022

Accepted 16 December 2024

KEYWORDS

Job tasks; probability of automation; routine intensity; training returns

1. Introduction

Many studies analysing the impact of technological change on labour markets reveal massive changes in the task content of jobs (Autor, Levy and Murnane 2003; for Germany e.g. Spitz-Oener 2006; Oesch and Menes 2011; Bachmann and Cim 2018). Since the 1970s, the importance of automatable manual and cognitive routine tasks has declined, while the importance of analytic and interactive non-routine tasks, the performance of which is assumed to be complemented by computers, has increased. Some of these trends appear to have levelled off since the mid-2000s (Bachmann and Cim 2018). One reason may be that the change in tasks due to the introduction of computer technologies has already taken place in many areas. However, recent technological advances, especially in artificial intelligence (AI), enable the automation of further tasks that were not considered as substitutable so far, such as truck driving (Brynjolfsson and McAfee 2014; Frey and Osborne 2017). Based on these new technological achievements, several studies have made predictions about (future) automation potentials. For instance, Frey and Osborne (2017) concluded that 47% of US employment is at high risk of being automated in the next 10–20 years, while other studies calculated lower shares based on different methodological approaches (see endnote 5), e.g.

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 Supplemental data for this article can be accessed online at <https://doi.org/10.1080/13639080.2024.2447037>

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Arntz, Gregory and Zierahn (2016) 9% for the US or Nedelkoska and Quintini (2018) 14% for the OECD. In any case, it seems plausible that the advances in AI may cause another wave of task change soon.

Education and further training are considered to be of great importance in this context, both in science (Autor 2015, 27; Heß, Janssen and Leber 2019) as well as in politics (Bundesministerium für Arbeit und Soziales and Bundesministerium für Bildung und Forschung 2019). For employees, who are the focus of this study, further training plays a particularly important role. It can help to keep pace with technological change and new skill and task requirements. For example, retraining (belonging to formal further training) can enable workers to move to another occupation that is in greater demand. Shorter courses, such as in-house training on the use of a new technology (belonging to non-formal further training), can also facilitate adaptation to new requirements and, for instance, enable the performance of new tasks within the same job. Finally, new technological possibilities allow increased digital, self-directed learning, e.g. on the computer (belonging to informal further training), which can as well be used to adapt skills to changing demands.

Further training appears to be particularly important for employees with a high share of tasks that can be automated (already or forthcoming). These workers are most at risk of facing wage or job losses due to technological change. Further training could enable them to perform more tasks that are complemented by new technologies and fewer tasks that are substitutable. Due to the expectable positive effects of a change in job tasks or the automation probability on wages and employment security (see e.g. Bachmann et al. 2022; Fossen and Sorgner 2022; Grigoli et al. 2020), further training could help to counteract possible negative consequences of digitalisation. These types of returns are very important but have hardly been considered in research so far.

The aim of this paper is to analyse the returns to different forms of further training, namely formal, non-formal and informal further training, for workers at risk of automation in Germany. For this purpose, two groups are considered, (a) workers with a high share of routine tasks according to the task-based approach by Autor, Levy and Murnane (2003) and (b) workers with a high automation probability according to Frey and Osborne (2017), taking into account recent developments in AI and mobile robotics and thus advanced automation possibilities. As returns to further training, (a) a change in job tasks towards less routine and more non-routine tasks and (b) a reduction in the probability of automation are examined, which is interpreted as adaptations to new demands due to technological change.

This paper is structured as follows. The next section provides an overview of different forms of further training activities and the current state of research. Section 3 is concerned with the theoretical background drawing on the task-based approach by Autor, Levy and Murnane (2003) and the human capital theory (G. S. Becker 1964). Section 4 describes the data used in this study, three waves (2011/2012, 2015/2016 and 2019/2020) of the starting cohort adults of the German National Educational Panel Study (NEPS) (Blossfeld, Roßbach and von Maurice 2011), and the methodology. Fixed effects models, controlling for unobserved individual heterogeneity, are used to relate changes in job tasks to further training activities between surveys. Section 5 presents the results. The paper closes with a summary and discussion of the results in Section 6.

2. Definition and state of research

Before discussing the current state of research and existing research gaps, a more detailed description of the forms of further training analysed is provided. In this article, further training is defined as the resumption of organised learning after completion of an initial education phase, usually marked by the entry into full employment (Deutscher Bildungsrat 1970, 197). As described above, there are different forms of further training, which can be distinguished according to their degree of formality, such as entire retraining programmes (formal), in-house courses (non-formal) or self-directed learning on computers (informal). This distinction is based on Eurostat (2016, 14–15), according to which

these forms of training can be defined as follows: Formal further training incorporates institutionalised, intentional learning planned by public organisations and recognised private institutions leading to officially recognised qualifications, such as studying at university. Non-formal further training describes institutionalised, intentional learning planned by an education provider, e.g. learning in courses or seminars. Finally, informal further training is intentional, but less organised and less structured learning, such as self-directed learning on the computer using learning programmes. Further training can be further differentiated, e.g. by content, organiser, duration or type of certification. Here, formal further training as well as job-related non-formal and informal further training are considered. Job-related means that the focus is on further training that has a professional purpose and is not undertaken for purely private reasons (e.g. a cooking course for people who do not need cooking skills in a professional context).

Concerning the returns to further training, most studies analyse the impact of training on wages (see Bassanini et al. (2007) for an overview), fewer on employment security (e.g. R. R. Becker 2019; Dieckhoff 2007) or other non-monetary returns (e.g. Andersen 2008; White and Knight 2018). Thereby, most studies focus on formalised forms of further training, while there have been only a few studies on the returns to informal further training (Rüber and Bol 2017), even though it makes up a significant proportion of adult learning activities.¹

So far, very little attention has been paid to the effect of further training on changes in job tasks and automation risks. Görlitz and Tamm (2016) analysed data from interviews with training voucher recipients in Germany in 2010/2011 and concluded that participation in work-related formal or non-formal further training significantly increases the scope of analytic non-routine tasks performed. Using German WeLL data from 2007–2010, Tamm (2018) found a significant positive effect of non-formal further training on interactive non-routine tasks. None of these studies found a significant negative effect of further training on substitutable routine tasks. Nedelkoska and Quintini (2018) focused on the automation risk according to Frey and Osborne (2017). They showed, based on data of the BIBB/BAuA Employment Survey 2012, that requalification leads to occupational skills with a lower risk of automation than the first qualification. However, they only considered formal training and their approach does not measure changes in the tasks composition of the job performed. Finally, in Zeyer-GlioZZo (2023), the effect of different forms of further training, including informal learning, on job tasks and the probability of automation for workers at risk of automation was examined with NEPS data for the period 2011 to 2015. The results indicate effects for routine, analytic and manual tasks with differences depending on the form of further training.²

In summary, there are only very few studies on the effects of further training on job tasks and the probability of automation, which are important outcomes in the context of current technological changes. They all cover a relatively short observation period and utilise somewhat older data, so that changes related to the latest technological developments such as AI may not yet be well reflected. In addition, informal further training has almost never been considered. Comparing the impact of formal, non-formal and informal further training on changing job tasks could provide important policy implications. Finally, there has been little research that has examined the effects of further training for employees at risk of automation. However, these workers are particularly vulnerable to technological change. Accordingly, the present findings contribute to a better understanding of the extent to which further training is helpful for the most important target group in the context of digitalisation.

3. Theoretical background and hypotheses

To explain why further training can help restructure job tasks and thereby reduce the risk of automation, the task-based approach, first developed by Autor, Levy and Murnane (2003), will be illustrated in more detail. This theoretical concept is used to derive hypotheses about the effects on job tasks and the risk of automation.

3.1. Task change of routine-intense workers

The main idea of the task-based approach is that jobs consist of a bundle of tasks and that output (goods or services) is achieved by using various skills for the execution of these job tasks (Autor, Levy and Murnane 2003). According to the theory, technological progress and falling computer prices have an impact on the labour market because computers can substitute workers in certain tasks while complementing them in others: So-called routine tasks that can be decomposed into clear rules are assumed to be performable by computers by following programmed code. Hence, workers can be substituted by machines for routine tasks and will carry out less of them as computer prices fall. Simple calculations are an example of cognitive routine tasks or repetitive assembly line tasks for manual routine tasks. In contrast, the performance of analytic and interactive non-routine tasks is expected to be complemented by computers, and the demand for these tasks is increasing. On the one hand, these tasks cannot be fully described by explicit rules for computer-based execution and, on the other hand, they often use routine inputs. Managing people or doing research belongs to this type of task. Workers carrying out manual non-routine tasks, such as janitorial or care services, can neither be complemented nor substituted by computers, so these tasks are not directly affected by technological progress.

Autor, Levy and Murnane (2003) make further assumptions about which workers perform which types of tasks. They assume that workers perform routine and non-routine tasks with varying degrees of productivity and that they choose their tasks according to comparative advantages. This means, for example, that if the wage for non-routine tasks is low compared to routine tasks, only workers who have a high relative efficiency in these tasks, i.e. who are much more productive in non-routine tasks compared to routine tasks, will perform them. Thus, labour supply for different tasks responds to changes in the relative wages for non-routine vs. routine tasks as well as to changes in the relative efficiency. To return to the example: If the relative price of non-routine tasks rises, it will also be worthwhile for some workers with lower relative efficiency to offer these types of tasks. They will then shift their labour supply from routine to non-routine tasks. Therefore, if the wage for non-routine tasks rises more than the wage for routine tasks or if workers become more productive in performing non-routine tasks (but not or to a lower extent in routine tasks, e.g. through the introduction of computers), some workers will reallocate their labour supply from routine to non-routine tasks.

In this paper, further training is assumed to be a mechanism to increase relative productivity in non-routine vs. routine tasks, thereby restructuring the labour supply. There are two reasons why one might expect this (see also Zeyer-Gliozzo (2023), Ch. 5.3.1)). (1) Autor, Levy, and Murnane (2003, 1309) suggest a comparative advantage for better qualified workers in performing analytic and interactive non-routine tasks vs. routine tasks. Following human capital theory (G. S. Becker 1964), qualification is part of a person's human capital. Investing in human capital, for example through further training (of any kind), increases the level of human capital and workers' productivity. Accordingly, further training should enhance qualification and thus also relative productivity in performing non-routine vs. routine tasks. (2) According to human capital theory, workers and firms will invest in further training only if the expected returns exceed the expected costs. They are therefore more likely to invest in training for tasks that will remain or increase in demand in the future rather than for tasks that can be automated. For this reason, further training should not only increase productivity in general, but especially productivity in the performance of non-routine tasks.

In sum, I expect that further training, whether formal, non-formal or informal, increases the relative productivity in analytic and interactive non-routine vs. routine tasks. Thus, for some workers providing routine tasks, further training would lead to a comparative advantage in the performance of non-routine tasks. They would then change their labour supply and offer non-routine tasks. Accordingly, I hypothesise that further training will decrease routine tasks (H1) and has a positive effect on analytic and interactive non-routine tasks (H2). While such changes can be expected for all forms of further training studied – formal, non-formal and informal further training – it can be

assumed that changes in tasks tend to be greatest as a result of formal further training (H3). This is because formal further training tends to be longer than non-formal courses and is also likely to be more extensive than informal learning activities. In addition, it leads to a further formal qualification which may, for example, enable a change of occupation.

Furthermore, I expect the effect of further training on job tasks to be largest for 'marginal workers'. Autor, Levy and Murnane (2003, 1288) define these as employees who are indifferent between supplying non-routine or routine work because their relative efficiency in non-routine vs. routine tasks is equal to the relative wage for routine work vs. non-routine work. I extend this definition to all employees who offer routine labour but are already comparatively productive at non-routine tasks and are therefore more likely to change labour supply than workers who are comparatively unproductive at corresponding tasks. Consider, for example, a bank teller who performs many routine tasks that can be automated, such as accounting or cashiering. If this person wants to reduce routine tasks in favour of non-routine tasks, such as advising customers, then further training – of any kind – is likely to be more helpful if they already have experience with such tasks or are otherwise relatively efficient at them. In other words, training is more likely to make them sufficiently efficient at counselling to make a change of task worthwhile. This is because their knowledge only needs to be extended rather than built up from scratch. Since highly skilled people should have a comparative advantage in non-routine tasks, highly skilled workers with many routine tasks should presumably be more efficient at non-routine tasks than less skilled routine workers. Moreover, skill accumulation through training is likely to be more productive for high-skilled workers (Heckman 1999).³ Thus, the effect of further training on job tasks is expected to be larger for high-skilled workers than for low-skilled workers (H4).

3.2. Task adaptations against the background of future developments

In Frey and Osborne (2017) popular (though also criticised) article on the automation risk of workers in the US in the next few decades, the authors recognised that advances in artificial intelligence and mobile robotics will expand the scope of tasks that can be performed by machines. Thus, some of the tasks that Autor, Levy and Murnane (2003) described as non-routine will become routine in the near future. They developed three so-called engineering bottlenecks that characterise the *new* limits of what is technically feasible: perception and manipulation tasks and tasks of social and creative intelligence. Examples include working in uncomfortable physical position for the first type of task, assisting for the second and originality such as reacting to unforeseen situations for the third task type. In addition, together with machine learning researchers, they categorise a subsample of occupations (70 out of 702) from the O*NET database as fully automatable or not automatable, given their job description and the latest technological advances.⁴ These two pieces of information (the automatability of jobs and the limits to automation in the form of engineering bottleneck tasks) were then combined using classification methodology to produce a prediction for the automation probability of occupations in the near future, leading to the result that 47% of the US employment is at high risk of automation.⁵

As technological development is progressing rapidly (Brynjolfsson and McAfee 2014) and the change in job tasks in terms of the task-based approach seems to have levelled off recently (Bachmann and Cim 2018), it is important to consider not only routine and non-routine tasks as defined by Autor, Levy and Murnane (2003) in connection with further training, but also the automation probability based on Frey and Osborne (2017). In line with the task-based approach and human capital theory, the same mechanisms of training effects can be expected here as above (Zeyer-Gliozzo 2023, Ch. 5.3.1): (1) Assuming that the better qualified also have a comparative advantage in the performance of (complex) social and creative intelligence tasks, and (2) against the background that employers and workers will only invest in training tasks that will remain or increase in demand, I hypothesise that further training has a positive effect on the scope of engineering bottleneck tasks and thus a negative impact on the probability of automation (H5). It

can be assumed that the demand for engineering bottleneck tasks will remain stable or increase because, according to Frey and Osborne (2017), these are the 'new non-routine' tasks, i.e. tasks that cannot be automated in the near future in the context of AI and mobile robotics. Therefore, the demand for workers performing them will remain or even increase if they are complementary to new technologies. This effect is again likely to be more pronounced for high-skilled workers (H6). In addition, here too the impact of formal further training is likely to be greater than that of non-formal and informal further training, although all forms of learning are expected to have an effect (H7).

4. Data and methodology

4.1. Data

The analyses are based on the National Education Panel Study (NEPS), starting cohort adults (SUF 12.1.0) (Blossfeld, Roßbach and von Maurice 2011; NEPS Network 2021), which provides longitudinal data on educational processes and competence development during the life course of adults. The target population consists of all persons born between 1944 and 1986 and living in private households in Germany.

Data from NEPS wave 3 (2011/2012), 7 (2015/2016) and 11 (2019/2020) are used, which are the survey years of job tasks ($N = 25192$).^{6,7} The sample studied includes individuals in paid, dependent employment aged 65 or less ($N = 16250$). Only persons for whom valid information was available (no missing or implausible values, 83.6%) in at least two consecutive interviews (waves 3 and 7 or 7 and 11, 72.0%) were included. The final sample consists of 9781 cases and 3956 individuals.

The provided cross-sectional weights were taken into account in all descriptive analyses. These weights adjust for different sampling probabilities due to the sampling design and non-response. In addition, the weights are calibrated to external benchmark distributions from the German Microcensus (Hammon et al. 2016). For the longitudinal analysis with fixed-effects regression models, the weights of the last wave (either wave 7 or 11) were considered. As the data do not provide appropriate longitudinal weights for the present analyses, the cross-sectional weights serve as an approximation.

4.2. Measurements

Job tasks were measured using an instrument developed by Matthes et al. (2014), which is directly based on the task-based approach. Most questions address how often respondents perform certain tasks, with responses ranging from 1 ('always/very often') to 5 ('very seldom/never'). For manual tasks, e.g. respondents were asked how often they have 'to stand continuously for at least 2 hours on an average working day'; or for interactive tasks how often they have to 'teach or train other people' (Matthes et al. 2014, 292 f.). For routine tasks, inversely, the frequency of performing complex non-routine tasks (difficult to automate), such as solving difficult problems or reacting to unforeseen situations, was asked. Accordingly, a low intensity of non-routine tasks indicates a high routine intensity. Analytic tasks, i.e. mathematics, reading and writing, were assessed with several questions on the complexity of the respective performance. For example, with regards to maths, respondents were asked whether they have to 'apply any mathematical skills or [...] have to deal with numbers' and if they answered yes, whether they 'have to perform any simple calculations such as adding things up or subtracting, multiplying or dividing them' (Matthes et al. 2014, 291). Thus, a variable for the complexity of maths use can be created, with values ranging from 1 'no numbers' to 5 'advanced math'.

The task variables (see Table A1 in the appendix) were used to calculate task indices for the following task types: analytic, interactive, manual and routine tasks. The task indices were constructed by first recoding the single items so that high values reflected high frequency or complexity

(values 0 to 4). Second, the items for an index were summed up and the mean value was calculated. The result was normalised to the range 0 to 1 (Matthes et al. 2014, 283, footnote 20).

To calculate the probability of automation, I follow Nedelkoska and Quintini (2018), who used the information on job automatability from Frey and Osborne (2017) and repeated their analyses at an individual level (based on PIAAC data). In this approach, information from the expert assessments of the automatability of occupations is combined with individual-level information on tasks performed. In doing so, a logistic regression model was used to estimate the automation probability as a function of job tasks corresponding to the engineering bottlenecks – perception and manipulation tasks and tasks of social and creative intelligence. Therefore, it is first necessary to find corresponding task variables. Table A2 in the appendix provides an overview of the task variables in O*NET used by Frey and Osborne (2017), in PIAAC used by Nedelkoska and Quintini (2018) and in NEPS used in the present study. This shows that the classifications are not entirely consistent across all three datasets, but there is a large overlap. Compared to the ‘original’ variables from O*NET, NEPS lacks information on manual/finger dexterity, fine arts practise or on negotiation or persuasion. However, there are other variables in the NEPS that cover the respective task categories, such as teaching or counselling for social intelligence tasks and various variables measuring originality for creative intelligence tasks (which overlap with the operationalisation in PIAAC). The data used to fit the model consisted of all respondents working in the occupations classified as fully automatable or non-automatable by Frey and Osborne (2017), based on the expert survey.⁸ Finally, the estimated coefficients of the logistic regression were used to predict the automation probability for all workers based on their individual values in the engineering bottleneck task variables.

Table 1 shows the results of the logistic regression.⁹ As outlined above, these are utilised to estimate an individual probability of automation, which is used for subsequent analyses. The coefficients for perception and manipulation, as well as several variables relating to social intelligence tasks (‘teaching’ and ‘assistance’, but not ‘advising’), have the expected sign and are significant.¹⁰ However, many of the coefficients of the variables relating to tasks involving creative intelligence are not significant and sometimes point in an unexpected direction, with the exception of ‘variety of requirements: can learn sth. new’. This indicates that the NEPS task items, which are based on the task-based approach by Autor, Levy and Murnane (2003), are not perfectly suited to capture engineering-bottleneck tasks, especially with regard to creative intelligence tasks. Consequently, the estimated automation probability may be biased upwards because their performance is not adequately measured. Nevertheless, the results indicate that the prediction of the automation probability is at least as good as the prediction of Nedelkoska and Quintini (2018, 44) (based on the area under the ROC curve).

As initially stated, workers at risk of automation are (a) workers whose jobs have a high routine intensity, or (b) who have a high probability of automation. The ‘routine intense’ variable is generated from the routine index and takes the value of 1 for all persons whose index is equal to or above the 75th percentile of the routine distribution (= 0.54) and 0 for all others (adapted from Heß, Janssen, and Leber (2019)). A worker is classified as having a high automation probability when having an automation probability above 0.7 (Frey and Osborne 2017, 265).¹¹

According to the definition given, further training is the resumption of learning after the completion of an initial educational phase. However, especially in the case of formal educational activities such as school attendance, it is difficult to distinguish between further training and activities of the first phase of education. Here, the gap between formal learning activities was used for this purpose.¹² The duration of the interruption, which distinguishes between the first and second education phases, was based on the criteria of the Bundesagentur für Arbeit (2021) for the promotion of further training (inspired by Kruppe and Trepesch (2017), 13 f.)). For persons who have (or do not have) a vocational qualification, the beginning of the second education phase is when there has been no formal learning for at least 12 (36) months.¹³ All subsequent activities after this gap, e.g. attending school, studying or completing vocational training, are considered to be part of the second education phase and thus of formal further training. Further training that does not lead

Table 1. Automatability as a function of engineering bottlenecks. Logistic regression.

	Logits	SE
Perception & manipulation: Uncomfortable physical position (ref.: very rarely/never)		
rare	−0.420*	(0.176)
sometimes	−0.614**	(0.219)
often	−0.940**	(0.202)
very often	−0.838**	(0.234)
Creative int.: Reacting to unforeseen situations (ref.: very rarely/never)		
rare	0.252	(0.466)
sometimes	−0.117	(0.466)
often	−0.005	(0.459)
very often	0.239	(0.471)
Creative int.: Doing things that have not been done before (ref.: very rarely/never)		
rare	−0.104	(0.213)
sometimes	−0.163	(0.236)
often	0.037	(0.285)
very often	0.051	(0.508)
Creative int.: Solving more difficult problems (ref.: very rarely/never)		
rare	0.291	(0.255)
sometimes	0.335	(0.250)
often	0.287	(0.257)
very often	−0.137	(0.302)
Creative int.: Having to learn something new (ref.: very rarely/never)		
rare	0.251	(0.417)
sometimes	−0.125	(0.412)
often	0.504	(0.428)
very often	0.401	(0.441)
Creative int.: Can learn something new (ref.: doesn't apply at all)		
doesn't really apply	0.044	(0.442)
applies to some extent	−0.537	(0.429)
applies fully	−0.885*	(0.450)
Creative int.: Wide variety of tasks changing frequently (ref.: doesn't apply at all)		
doesn't really apply	0.345	(0.343)
applies to some extent	−0.146	(0.344)
applies fully	−0.050	(0.361)
Social int.: Teaching/training (ref.: very rarely/never)		
rare	−0.367*	(0.183)
sometimes	−0.542**	(0.189)
often	−0.468*	(0.214)
very often	−1.229**	(0.292)
Social int.: Advising (ref.: very rarely/never)		
rare	−0.073	(0.210)
sometimes	−0.373	(0.236)
often	−0.166	(0.204)
very often	−0.036	(0.234)
Social int.: Customer contact (ref.: very rarely/never)		
rare	−0.215	(0.434)
sometimes	−0.631	(0.438)
often	−0.698+	(0.394)
very often	−0.393	(0.385)
Social int.: Assistance (ref.: very rarely/never)		
rare	−0.297	(0.208)
sometimes	−0.277	(0.224)
often	−0.909**	(0.220)
very often	−2.658**	(0.303)
Social int.: Job interviews (ref.: very rarely/never)		
rare	−0.337+	(0.187)
sometimes	−0.284	(0.220)
often	−0.241	(0.272)
very often	1.059**	(0.327)

(Continued)

Table 1. (Continued).

	Logits	SE
N	1510	
Pseudo R ²	0.223	
Correctly classified	73.77%	
Area under the ROC curve	0.809	

Source: NEPS SC6 wave 3, unweighted, Note: Robust standard errors in parentheses. Significance Level: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$. Own calculations.

to a formal qualification (operationalised by the information on the type of training) or that only leads to a certificate of attendance is not counted. Variables were generated indicating whether at least one formal training was attended between waves 3 and 7 and between waves 7 and 11.

Data on non-formal further training have been collected in NEPS through different question modules: The module *spCourse* contains information on training participation since the last interview during different episodes, e.g. employment, unemployment or parental leave. As the focus is on job-related further training and on people at work, only training courses during employment episodes are taken into account.¹⁴ The second module providing information on non-formal further training is *VocTrain*. Some of the courses reported there, mainly courses for obtaining a licence, can also be classified as further training (FDZ-LifBi (2021), 120). Since obtaining a licence usually also has a professional purpose, this further training is also classified as job-related. Finally, all additional courses, collected in the module *spFutherEdu1*, that were undertaken for professional or both professional and private purposes, are taken into account.¹⁵ Again, variables have been created that indicate whether a person has participated in non-formal further training between the corresponding four waves.

To operationalise informal further training, information on the 'Visit of special trade fairs or congresses', 'Visit of special lectures' and 'Use of any computerized learning programs, learning CDs or DVDs or similar materials' was used.¹⁶ The respective informal learning activity was only considered if it was undertaken for professional or professional and private reasons. A variable was created to indicate the performance of informal further training, which is equal to 1 if at least one of the activities has been carried out since the last four waves.¹⁷

For the longitudinal analyses, training variables are created that are equal to 1 when the first further training activity is attended and remain 1 in the following wave considered (as the effect of the training is assumed to be lasting).

Table 2 presents summary statistics, including all control variables, for the whole sample, for routine intense and not routine intense workers as well as for workers with and without a high probability of automation.¹⁸

4.3. Estimating the returns to further training

Human capital returns (job tasks and the probability of automation) of individual i at time t (2011, 2015, 2019) are modelled linearly as a function of training participation $\mathbf{w}_{it}$ (formal, non-formal and informal further training), a vector of controls $\mathbf{x}_{it}$, a time constant error term a_i and an idiosyncratic error term u_{it} :

$$y_{it} = \mathbf{w}_{it}'\alpha + \mathbf{x}_{it}'\beta + a_i + u_{it} \quad (1)$$

A crucial problem in estimating the returns to further training is the selectivity into training (Bassanini et al. 2007, 254 f.). When using ordinary least squares estimators, the explanatory variables must be uncorrelated with the error term ($a_i + u_{it}$) to obtain unbiased coefficients. If there are unobserved characteristics that have an impact on training participation and on the returns to training, results would be biased (Wooldridge 2013).

Table 2. Sample characteristics.

Mean/%	All		Routine intense		Not routine intense		High automation probability		No high automation probability	
	sd	mean/ %	sd	mean/ %	sd	mean/ %	sd	mean/ %	sd	
Woman (%)	46.46	49.88	51.42	49.99	43.73	49.61	57.05	49.52	44.18	49.66
Age in years	46.40	9.40	47.72	9.21	45.67	9.42	45.99	9.23	46.48	9.43
At least Abitur (%)	34.42	47.51	19.99	40.00	42.37	49.42	34.85	47.67	34.32	47.48
Children in household (%)	52.08	49.96	53.83	49.86	51.12	49.99	53.06	49.92	51.87	49.97
Married (%)	64.93	47.72	69.59	46.01	62.36	48.45	65.97	47.40	64.71	47.79
Born in Germany (%)	82.18	38.27	74.78	43.44	86.25	34.43	81.48	38.86	82.33	38.15
Fixed-term contract (%)	4.69	21.13	4.53	20.79	4.77	21.32	4.84	21.47	4.65	21.06
Working experience in years	23.64	10.22	24.63	10.05	23.10	10.28	22.61	9.97	23.87	10.26
Computer usage at work (%)										
No computer use	17.28	37.81	31.76	46.56	9.30	29.05	22.74	41.93	16.10	36.76
Standard computer use	54.08	49.84	52.98	49.92	54.69	49.78	54.20	49.84	54.06	49.84
Complex computer use	28.63	45.21	15.26	35.97	36.01	48.01	23.06	42.13	29.84	45.76
Actual working hours per week	36.75	12.29	32.88	13.33	38.89	11.11	33.51	12.82	37.45	12.05
Professional requirement level (%)										
Unskilled or semi-skilled activities	8.46	27.84	15.25	35.95	4.72	21.21	15.26	35.97	6.99	25.51
Specialist activities	60.01	48.99	69.90	45.88	54.55	49.80	67.39	46.89	58.41	49.29
Complex specialist activities	12.72	33.32	8.41	27.76	15.09	35.80	9.34	29.11	13.45	34.12
Highly complex activities	18.81	39.08	6.44	24.55	25.63	43.66	8.01	27.15	21.15	40.84
Sector (%)										
Manufacturing	34.92	47.67	33.44	47.19	35.74	47.93	36.86	48.26	34.50	47.54
Economic services	33.83	47.32	36.36	48.11	32.43	46.81	40.47	49.10	32.39	46.80
Public and personal services	30.36	45.98	28.55	45.17	31.36	46.40	20.48	40.37	32.50	46.84
Other industries	0.89	9.40	1.65	12.75	0.47	6.84	2.19	14.63	0.61	7.79
Civil service (%)	25.22	43.43	23.07	42.14	26.40	44.09	18.22	38.61	26.73	44.26
Company size (%)										
Less than 10 employees	14.41	35.12	17.97	38.40	12.44	33.01	15.45	36.15	14.18	34.89
10 to under 200 employees	48.73	49.99	52.48	49.95	46.66	49.89	47.23	49.94	49.06	49.99
200 employees or more	36.86	48.25	29.55	45.64	40.90	49.17	37.32	48.38	36.77	48.22
Real gross monthly wage in Euro with 2015 prices	3117.35	2731.93	2385.16	3058.72	3521.21	2441.81	2671.86	4059.05	3213.70	2337.51
Number of employees managed (%)										
0 employees	74.69	43.48	82.48	38.02	70.39	45.66	85.67	35.05	72.31	44.75
1–2 employees	4.52	20.78	4.29	20.26	4.65	21.06	3.14	17.46	4.82	21.42
3–9 employees	11.78	32.24	8.23	27.49	13.73	34.42	7.27	25.97	12.75	33.36
10 or more employees	9.01	28.64	5.00	21.79	11.23	31.57	3.92	19.41	10.11	30.15
Health satisfaction (0–10)	7.35	1.82	7.34	1.86	7.36	1.80	7.42	1.88	7.34	1.81
Occupation-related work experience in years	16.74	10.93	16.92	10.86	16.64	10.97	15.35	10.46	17.04	11.01
N	9781		2735		7046		1577		8204	

Source: NEPS SC6 wave 3, 7 and 11, weighted. Note: All occupational and workplace characteristics refer to the occupation in the context of which information on job tasks was provided.

The training literature has used various methods to address this problem, such as Fixed-Effects (FE) estimation (e.g. Bassanini et al. 2007; Rüber and Bol 2017), counterfactual research designs (e.g. Görlitz and Tamm 2016; Leuven and Oosterbeek 2008) or estimation with instrumental variables (e.g. Kuckulenz and Zwick 2003). Here, the temporal variation in further training and job tasks was exploited to follow the first approach. In FE models, equation (1) is averaged over time. The averaged values are then subtracted from equation (1) for each t (Wooldridge 2013). This removes all time-

invariant variables from the equation. Consequently, the FE estimation allows for a correlation between the time-invariant unobserved variables (captured in a_i) and the explanatory variables.

Measurement errors, time-varying, unobserved heterogeneity and reverse causality can still lead to biased estimates (Brüderl 2010, 992). The latter may be an issue here (see also Zeyer-Gliozzo 2023). For example, an employee may first be given new tasks (e.g. as a result of a promotion) and then be expected to acquire the necessary skills, e.g. through attending further training. This is not unlikely, particularly in the case of informal further training, which can be one form of familiarisation. However, the higher the level of formalisation of training, the less likely this problem seems to be. In Germany, formal educational qualifications are often a prerequisite for the exercise of certain tasks or professions and must therefore be acquired beforehand (e.g. in order to be allowed to work as a police officer, one must first complete the appropriate vocational training). Moreover, due to a lack of information, an employer may not be able to assess with certainty whether the worker can perform the new tasks satisfactorily. For workers who have previously performed many routine tasks, the employer is likely to have incomplete information about their ability to perform non-routine tasks. In order to ensure the quality of the output, it seems reasonable that the worker should complete an appropriate training course *before* changing tasks. For example, if a painter has previously painted vehicles by hand, but this is now automated by using a new machine, he or she should first learn how to handle this machine, e.g. in a course, before operating it. Nevertheless, possible reverse causality should be kept in mind when interpreting the results, especially the estimates for informal further training.

5. Results

5.1. Effects of training participation on job tasks and the probability of automation

Before looking at the returns to the different forms of further training for workers at risk of automation, it is described to what extent these were attended over the period considered. Table 3 presents data on the participation in formal, non-formal and informal further training between 2011 and 2015 as well as 2015 and 2019 for all, routine intense and not routine intense workers as well as for workers with and without a high probability of automation. The most common form of further training among all employees is non-formal further training (e.g. 62% between 2011 and 2015), followed by informal further training (51% between 2011 and 2015).¹⁹ Considerably fewer workers participated in formal further training (only 7% between 2011 and 2015).

Comparing routine intense and not routine intense workers shows that the former participated less frequently in all three types of further training. The differences are greatest regarding informal further training. For example, between 2011 and 2015, 31% of routine intense workers participated in at least one informal training activity, while the proportion among not routine intense workers was almost twice as high (61%). Participation in training by employees with and without a high automation probability shows similar patterns, although the differences regarding non-formal and informal further training are less pronounced.

To better interpret the size of the possible effects of further training on job tasks and the probability of automation, it is worth looking at their averages and changes between 2011, 2015 and 2019 (see Table 4). This shows that the shift in job tasks between these years was not particularly pronounced. Across all employees, there was a slight decrease in the intensity of manual as well as analytic and interactive tasks. Meanwhile, the average routine intensity and automation probability increased slightly. This confirms the trend that the increase in cognitive non-routine tasks and the decrease in routine tasks have weakened or even reversed since the mid-2000s (Bachmann and Cim 2018).

For routine intense workers, the amount of substitutable tasks performed decreased between 2011 and 2015, but then increased again. At the same time, the share of analytic and interactive non-

Table 3. Average training participation since the last four years in percent.

	All				Routine intense		Not routine intense		High automation probability		No high automation probability	
	2011–2015	2015–2019	2011–2015	2015–2019	2011–2015	2015–2019	2011–2015	2015–2019	2011–2015	2015–2019	2011–2015	2015–2019
Formal training	6.83	4.08	5.20	3.61	7.67	4.37	7.60	2.76	3.14	2.76	7.60	4.39
Non-formal training	62.45	59.96	47.76	45.66	69.94	68.79	64.07	44.99	54.63	44.99	64.07	63.42
Informal training	51.32	48.12	31.39	28.94	61.49	59.97	54.13	32.41	37.82	32.41	54.13	51.76
N	2879	2946	798	813	2081	2133	2429	492	450	492	2429	2454

Source: NEPS SC6 wave 3 to 11, weighted.
The survey of non-formal and informal training changed slightly between 2011 and 2015 and 2015 and 2019 (see manuscript). Accordingly, the values can be compared only limitedly over the years.



Table 4. Mean of job tasks indices and the probability of automation in 2011, 2015, and 2019.

	All			Routine intense			Not routine intense			High automation probability			No high automation probability		
	2011	2015	2019	2011	2015	2019	2011	2015	2019	2011	2015	2019	2011	2015	2019
routine	0.46	0.47	0.50	0.67	0.64	0.65	0.35	0.38	0.41	0.59	0.57	0.60	0.43	0.45	0.48
analytic	0.53	0.53	0.50	0.40	0.39	0.39	0.59	0.60	0.57	0.42	0.44	0.41	0.55	0.55	0.52
interactive	0.44	0.44	0.40	0.34	0.33	0.33	0.49	0.49	0.45	0.25	0.28	0.30	0.47	0.47	0.43
manual	0.34	0.32	0.33	0.38	0.38	0.36	0.32	0.29	0.31	0.24	0.24	0.23	0.36	0.34	0.35
automation probability	0.47	0.47	0.50	0.57	0.56	0.59	0.42	0.42	0.45	0.79	0.68	0.65	0.40	0.43	0.47
N	2879	3956	2946	798	1124	813	2081	2832	2133	450	635	492	2429	3321	2454

Source: NEPS SC6 wave 3, 7, and 11, weighted. Note: A high routine intensity/automation probability refers to the first considered wave of a respondent.

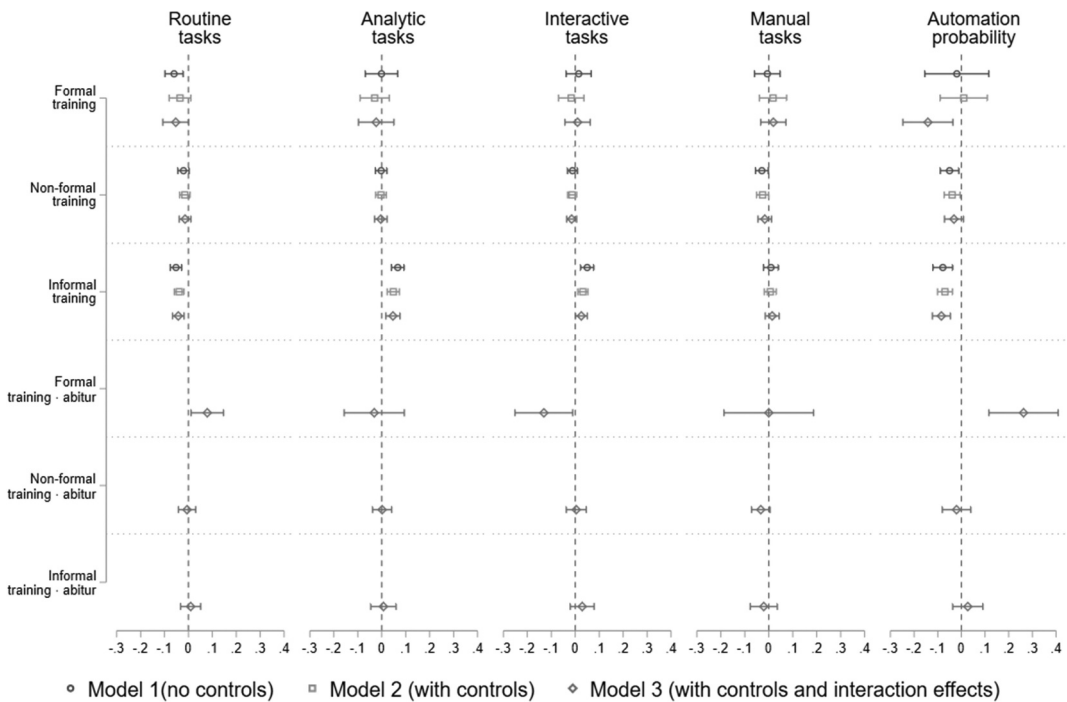


Figure 1. The on job tasks and the automation probability for workers at risk of automation (90% confidence interval). Source: NEPS SC6 waves 3, 7 and 11, weighted. *Notes:* Coefficients of fixed effects regressions. The sample comprises employees who had routine intense jobs/high automation probability (last column) in the first survey considered. Model 1 includes year dummies. Model 2 and 3 also include computer use at work, change of job, KldB requirement level, fixed-term contract, working experience, unemployment episode during the last four years, sector, civil service, company size and having children in the household and being married (both interacted with gender).

routine tasks decreased slightly. On average, therefore, these workers have not experienced a change in tasks that would appear to be favourable in the context of technological change. The situation is different for employees with a high probability of automation. Their average automation probability decreased both from 2011 to 2015 and (to a lesser extent) from 2015 to 2019.

The results of the FE regressions measuring the effects of further training on tasks and the automation probability of workers in routine intense jobs (first four columns) and with a high automation probability (last column) are shown in Figure 1.²⁰ The first set of analyses (Model 1) controls for period effects only. The results show that it is particularly beneficial to undertake informal further training in the context of digitalisation. Participation in at least one informal learning activity reduced the amount of automatable routine tasks and increased the intensity of non-routine tasks for employees with above-average routine tasks. Furthermore, the probability of automation decreased after participation in informal further training for employees who initially had a high likelihood of being automated. Thus, informal training helped workers at risk of automation to focus less on substitutable tasks and more on tasks that are not automatable but even complementary to new technologies. The effect sizes cannot be considered small, as the effects (0.05–0.07 index points / 8% points) are considerably larger than the average changes in job tasks and automation probability of workers at risk of automation between 2011 and 2019.

In the case of non-formal further training, there are desirable significant effects, particularly on the automation probability, which decreased by 5% points on average after participation in training. There is also a negative effect on routine tasks (0.02 index points), but this is not significant. However, participation in at least one non-formal further training reduced the amount of manual tasks, some of which can also be substituted.

Finally, participation in at least one formal further training course reduced the intensity of routine tasks, but had no significant effect on any other type of task or on the likelihood of automation. The effect on routine tasks is greater than the effect of any other form of further training, but the differences are not significant.

When controls are included (Model 2), the training coefficients decreased slightly. Thus, the control variables explain part of the relationship found. All effects remain significant except for the effect of formal further training on routine tasks, which became non-significant. Thus, the results support the hypotheses of negative training effects on routine tasks and positive effects on non-routine tasks (H1 and H2) only for informal further training, while the hypothesis of negative effects on the probability of automation (H5) can be confirmed for non-formal and informal further training. There are no stronger effects of formal further training than of less formalised forms of further training (H3 and H7).

In Model 3, interaction effects were included to test whether the effects of further training are stronger for high-skilled workers than for low skilled-workers. In the case of non-formal further training, there is at least a tendency in this direction. High-skilled workers who participated in non-formal further training were able to reduce automatable tasks more than low-skilled workers. However, the interaction effects are not significant.

A partly opposite trend emerges with regard to formal and informal further training. For example, low-skilled workers at risk of automation showed a greater reduction in the probability of automation after formal further training than high-skilled workers, for whom an opposite effect was observed. Informal learning was also partly more beneficial for low-skilled workers (in terms of routine tasks and the probability of automation). However, the interaction effects of informal further training are not significant either. Overall, therefore, the hypotheses of a greater training benefit for high-skilled workers cannot be confirmed, neither with regard to a change in job tasks (H4) nor with regard to a reduction in the probability of automation (H6).

5.2. Additional analysis and robustness of findings

To address the problem of possible time-varying unobserved heterogeneity, additional controls were included in the regression models: income, leadership (both serving as proxies for promotion), health satisfaction and work experience in the respective occupation. The estimated effects changed only little when these variables were controlled for, and in some cases became even stronger (see Section C.1 and Table A6 in the appendix). Thus, unobserved factors such as career advancement have not biased the effects of further training on job tasks.

In order to reduce the problem of reverse causality, (1) further training prior to the respective task change (e.g. further training between 2010 and 2011 for task changes between 2011 and 2015, Table A7 in the appendix), and (2) further training within the first two years between the survey periods (e.g. training between 2011 and 2013 for task changes between 2011 and 2015, Table A8 in the appendix) were taken into account. The second method supports the results presented, particularly for non-formal further training. The effects for informal further training are somewhat smaller and subject to more uncertainty, except for the reduction in the probability of automation. If further training prior to the task change is taken into account, the effects and significances differ more strongly. However, both approaches run the risk of underestimating the effect of further training because the potential time lag between training and task change is longer (see appendix C.2 for a discussion). Therefore, the results cannot completely rule out reverse causality, but the second part of the analyses may reduce this problem. Furthermore, they show that further training does not have a delayed effect on task changes.

As described above, informal further training was measured by carrying out at least one of three activities – attending trade fairs or congresses, attending lectures and using computer-based learning programmes, learning CDs or DVDs or similar materials.²¹ In contrast to the measurements of formal and non-formal further training, this only covers a few and specific forms of informal

learning, leaving out many others, such as learning from colleagues or vocational learning through reading literature. It is therefore worth taking a closer look at which of these activities primarily caused the previous results. Their individual effects have been analysed in further models (Tables A9 and A10 in the appendix). These show that of the forms of informal further training analysed, learning with media plays the greatest role in a change of job tasks, as the main effects are larger for this type of learning (although only significant for the automation probability).

The effects of further training on job tasks were additionally calculated only for completed formal and non-formal further training (Table A11 in the appendix). The results changed very little and the main conclusion regarding automatable/non-automatable tasks remains the same.

Finally, the heterogeneity in the amount of further training was considered by including the duration of completed formal further training and the number of completed non-formal further training (Table A12 in the appendix). In the case of formal further training, it is partly evident that the longer the courses, the smaller the effects, e.g. on the likelihood of automation. This is probably related to the type of further training. Completed formal further training in the form of other courses, apprenticeships or courses at associations/chambers lasts on average shorter than, for example, a technician/master's degree, study or doctorate. This result is therefore in line with the observed interactions with education, as among high-skilled workers at risk of automation, formal further training most often included studying, while for the reference group with lower qualifications, other courses were most common (followed by apprenticeships in both cases). The result may therefore reflect who the formal further training helps (upgrading/retraining for the low-skilled) rather than the actual duration. Nevertheless, the case numbers for formal further training are small, so the results should be treated with caution. For non-formal further training, more courses tend to have a greater impact, for example on routine tasks or the automation probability, but the effect is small and not significant. Overall, however, the results are not entirely consistent, e.g. the duration of formal further training does not matter for analytic tasks, and the number of non-formal further training courses weakens the (still small and non-significant average) effect of non-formal further training on interactive tasks.

6. Summary and discussion

The main objective of this study was to analyse the extent to which formal, non-formal or informal further training leads to a change in tasks towards less automatable and more non-automatable tasks and to a reduction in the probability of automation. This can be interpreted as an adaptation to technological change. The focus is on workers at risk of automation, i.e. (a) workers with many substitutable routine tasks (≥ 75 th percentile) or (b) with a high probability of automation ($> 70\%$), in order to analyse the benefits of further training for those who may be particularly threatened by technological progress.

Using German NEPS data from 2011, 2015 and 2019, FE regressions show that the hypotheses of a negative effect of further training on routine tasks (H1) and a positive effect on analytic and interactive non-routine tasks (H2) can be clearly confirmed only for informal further training. In addition, the results confirm negative effects of non-formal and informal further training on the probability of automation (H5). Formal further training only had a significant negative effect on routine tasks when control variables were not included. This effect was larger, although not significantly, than the effects of non-formal and informal further training. Therefore, the hypotheses of a larger effect of formal training cannot be confirmed (H3 and H7). The effects decreased with the inclusion of control variables, although some of them, such as job change, may also be a mechanism (especially for formal further training).

There was also a tendency for the effects of further training to be somewhat heterogeneous between high-skilled and low-skilled workers, depending on the type of training. Non-formal further training tends to have a greater effect on changes in job tasks for high-skilled workers, while this

group partly benefits less from formal and informal further training. However, the results are not entirely consistent and mostly not significant. Thus, the hypotheses of greater effects of further training on job tasks and the probability of automation for high-skilled workers (H4 and H6) cannot be confirmed.

Overall, I conclude that participation in further training – especially informal learning (particularly with media, as supplementary analyses indicate) – can indeed help to keep up with new demands and to adapt one's tasks as digitalisation progresses. The effects of informal further training on routine tasks (0.04) and the probability of automation (6.9% points) are not negligible when compared to the overall changes in job tasks and automation risks between 2011 and 2019. The finding that less formalised further training is helpful suggests that adjustments to digitalisation do not require retraining *per se* but can also be managed through smaller skill adjustments – including self-directed ones.

The lower effect of non-formal compared to informal further training found in many cases may be explained by the fact that many different forms of further training are subsumed here, which may cancel out existing effects of specific forms of non-formal further training. For example, Tamm (2018) showed that the content of non-formal training plays a role and the results of Zeyer-GlioZZo (2023) indicate that effects can differ depending on who financed the training (individual or company).

The present result contrasts with previous studies that found positive effects of non-formal further training on non-routine tasks (Görlitz and Tamm 2016; Tamm 2018). However, these studies did not focus on workers at risk of automation. The findings on the relationship between further training and a task change between 2011 and 2015 are largely confirmed, particularly with regard to the importance of informal training (Zeyer-GlioZZo 2023). Larger effects were, however, found for changes in the probability of automation. This may be due to the fact that the impact of further training on task changes in the context of AI has increased over time as adaptations related to these technologies have become more important.

In evaluating and interpreting the results, one has to bear in mind that in some cases the results were not or only weakly significant. Nevertheless, they indicate a tendency. For informal further training it is important to consider the possibility of reverse causality. However, this problem could be reduced with additional analyses and robust results could be obtained regarding the impact on the probability of automation. Nevertheless, further training seems to have only a short-term effect on the change of job tasks. Viewed cautiously, though, this result should be interpreted as correlation rather than causal effect. In this respect, studies with further methods for estimating causal effects are recommended. Furthermore, only average effects were considered for formal and non-formal further training. As in the case of informal further training, where particularly learning with media seems to play a role in changing tasks, there could be different effects depending on the type or topic (see above). At the same time, only a few forms of learning were considered for informal further training. For example, learning from colleagues was not explored at all. Further research on these points is recommended. In addition, it may also be of great interest to consider further heterogeneities, not only according to characteristics of the employees, as was done here, but also, for example according to occupational groups or sectors depending on how strongly they are affected by automation.

The current results support that specific forms of further training are relevant for workers at risk of automation to keep pace with technological change. Given that previous studies have shown a correlation between job tasks and further training participation in favour of workers who are not at risk of automation (more non-routine tasks, fewer routine tasks, lower automation probability), this is a highly relevant finding (e.g. Kleinert and Wölfel 2018; Mohr, Troeltsch and Gerhards 2016; Nedelkoska and Quintini 2018; Zeyer-GlioZZo 2023). However, the results show how important it is to take a closer look at these issues when making policy decisions. Calling for more further training in general may not be that effective, as not every form of further training (for not every type of worker) is helpful. The results suggest that in order to support this target group, self-directed informal learning offers should be promoted in particular.

Notes

1. German data from the Adult Education Survey from 2018 show that 45% of the 18–64 year olds engage in informal learning activities, while 54% participate in non-formal and only 4% in formal further training (Autorengruppe Bildungsberichterstattung 2020, Tab. G2-1 web).
2. The analyses in the dissertation by Zeyer-Gliozzo (2023) are further developed and supplemented in the present study, including a longer observation period with more recent data.
3. This follows the 'skill begets skill' argument (Heckmann 1999, 42), meaning that the returns to investments in human capital should be higher for highly skilled than for less skilled. This is because they are presumed to be more productive in human capital accumulation, allowing greater productivity gains through education.
4. The O*NET data provide standardised descriptions of occupations in the US (O*NET Resource Center 2020).
5. However, this estimation has been criticised because it estimates the risk of automation at the occupational level while ignoring task differences within occupations (Arntz, Gregory, and Zierahn 2016, 7). This problem can be addressed by calculating the probability of automation not on the basis of information about tasks in entire occupations, but at the level of individuals, i.e. on the basis of information about the tasks actually performed by a person. By doing so, other authors estimate a much lower proportion of individuals in the US at high risk of automation (e.g. Arntz, Gregory, and Zierahn 2016). This paper also adopts an approach at the level of individual job tasks.
6. For the sake of simplicity, I will only refer to the years 2011, 2015 and 2019 in the following.
7. Persons from the refreshment sample in wave 3 are considered from wave 7 at the earliest, as they were not asked about job tasks in wave 3.
8. Occupations had to be transferred from O*NET to ISCO-08, which I adopted from Nedelkoska and Quintini (2018, 121 f.). Seven occupations were not transferable, so only 63 occupations were used.
9. The underlying sample includes all individuals who participated in wave 3, had no missing values for the task variables used, and worked in occupations that are manually labelled as automatable or not automatable.
10. Some coefficients for 'customer contact' and 'job interviews' were also in the expected direction and weakly significant. However, compared to very rare or no discussions with applicants or claimants ('job interviews'), very frequent job interviews were positively associated with the automation probability.
11. Figure A1 in the appendix shows the distribution of the routine index and the automation probability including the classification of workers as being at high risk of automation.
12. Military service and vocational preparation schemes are not included in the interruption period.
13. According to §81 Para. 2 Sentence 1 SGB III, all persons who have successfully completed formal training of at least two years are considered to have a vocational qualification.
14. 97% of the training courses in this module took place during employment. Further training during other periods can also be for non-work purposes, which is the case for almost a third of these courses. If these courses are also taken into account, the results change only slightly and the main conclusions remain the same.
15. The reason for course attendance was asked in the questionnaire. However, until wave 9, this information was only collected for a random selection of courses, which means that until then the number of courses from this module was systematically lower than the actual number of courses reported. Nevertheless, more than 60% of the further training reported was for purely private reasons.
16. Since the last two waves, respondents have also been asked about informal training through the use of learning opportunities on the internet or via apps (e.g. wikis, online forums, podcasts or YouTube). These forms of learning were also included in the analysis. However, they are not part of the data for the years 2009–2017, although respondents may have partially reported them under 'computerized learning programs'. Excluding these forms results in slightly smaller effects, but all conclusions remain unchanged.
17. The measurement of further training is not based on existing constructs but was developed for the NEPS survey (see Janik, Wölfel and Trepesch (2016) for more details).
18. Table A3 in the appendix lists the values and the ranges of all control variables.
19. Some studies find a more frequent participation in informal than in non-formal further training in Germany (e.g. Fialho, Quintini, and Vandeweyer 2019, 37). However, in the case of informal learning, the survey methods sometimes differ significantly between datasets. For example, Fialho, Quintini, and Vandeweyer (2019, 29) use PIAAC data and operationalise informal learning according to whether at least one of the following activities was undertaken at least once a week: learning from co-workers or supervisors, learning by doing, or keeping up to date with new products. This differs considerably from what is measured in the present study.
20. Table A4 in the appendix shows the coefficients of Models 1 and 2 and Table A5 in the appendix shows the coefficients of Model 3.
21. In the last two years, the use of learning opportunities on the internet or via apps has also been included in the measurement of informal learning, see endnote 16.

Acknowledgments

The author would like to thank Martin Werding for his thoughtful feedback on earlier drafts of this paper and Martina Brandt and Jakob Schwerter for insightful discussions and constructive feedback. The author also acknowledges the two anonymous reviewers for their valuable and constructive suggestions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The project “From Prediction to Agile Interventions in the Social Sciences (FAIR)” has received/is receiving funding from the programme “Profilbildung 2020”, an initiative of the Ministry of Culture and Science of the State of Northrhine Westphalia. The sole responsibility for the content of this publication lies with the authors.

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Data availability statement

This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort 6 – Adults, doi:10.5157/NEPS:SC6:12.1.0. From 2008 to 2013, NEPS data were collected as part of the Framework Programme for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, the NEPS survey has been carried out by the Leibniz Institute for Educational Trajectories (LifBi) at the University of Bamberg in cooperation with a nationwide network.

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